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NeuroTwinceutics™ as a Neuromorphic Digital Twin Model for Predictive and Personalized Pharmacotherapy

Hamed Nozari[a*]
[a]*Senior Researcher in Optimization and Digital Transformation, Bio10, UAE*

Abstract

The evolution of digital and computational technologies has provided new opportunities for the design of intelligent therapeutic systems. The present study introduces an innovative framework called NeuroTwinceutics™, which is based on the integration of human-centered digital twins and neuromorphic computing architecture. Aiming to simulate and predict individual drug responses under variable biological and psychological conditions, this model consists of three main components: NeuroCore (neuromorphic processing core), TwinEngine (digital representation of the body), and Pharmaco-Loop (pharmaceutical feedback loop). To evaluate the initial performance of this framework, synthetic data for a hypothetical patient was generated and used in an antidepressant drug treatment scenario. The results showed that the model is capable of adaptive analysis, predicting psychological fluctuations, and providing timely intervention suggestions. Features such as real-time processing, adaptability, and scalability to industrial scale (such as controlling bioreactors) are among the strengths of this framework. The findings suggest that NeuroTwinceutics could be an effective step towards realizing intelligent personalized medicine.

Keywords*:* Digital Twin, Neuromorphic Computing, Personalized Pharmacotherapy, Adaptive Simulation, Smart Biomedicine

1. Introduction

The transformation of the healthcare and pharmaceutical industries in recent years has been driven more than ever by the use of digital technologies, simulation, and artificial intelligence. One of the key concepts that has gained a special place is the digital twin technology, which is designed to provide a virtual, continuous, and accurate representation of physical systems [1]. In the medical field, digital twins have opened up new horizons for patient modeling, disease prediction, and evaluation of the effects of therapeutic interventions [2], especially in a context where personalized treatment has become an essential need [3].

In parallel with these developments, neuromorphic computing technology has emerged as a new generation of processing architectures that, inspired by the way the human brain processes data, are capable of adaptive learning, real-time decision-making, and complex nonlinear data analysis [4]. This approach has advantages over traditional AI models such as lower energy consumption, faster response time, and better generalization in changing conditions [5].

Despite the significant development of digital twins in medicine, many existing models are still based on static structures or non-dynamic deep learning algorithms [6], and lack the ability to adapt to real-time biological and behavioral

[*]Corresponding author.
E-mail address: h.nozari@iau.ac.ae
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conditions of patients. In such a context, the need for a new framework that can harness the power of neuromorphic to create dynamic and adaptive digital twins is increasingly felt.

To address this need, the present study introduces a conceptual and operational framework called NeuroTwinceutics™. This framework provides an innovative combination of human-centric digital twin and neuromorphic architectures that are capable of real-time simulation and accurate prediction of individual drug responses based on multimodal physiological, behavioral, and pharmacological data. In this model, components such as NeuroCore (neural processing core), TwinEngine (digital body simulation engine), and Pharmaco-Loop (pharmacodynamic feedback loop) interact in a structured manner to create a living and intelligent digital patient profile.

What distinguishes this study from previous studies is not only the introduction of a new conceptual model, but also its initial implementation with simulated data and the evaluation of adaptive analysis capabilities in semi-real conditions. Also, given the scalability of the presented architecture, horizons for its use on an industrial scale, including in pharmaceutical bioreactors and biomanufacturing processes, have been investigated in this study.

The structure of this paper is as follows: In the second section, a review of previous studies and the position of neuromorphic models and digital twins in health is presented; In the third section, the conceptual framework of NeuroTwinceutics is introduced and explained; In the fourth section, the architecture and methodology of the model are explained; and In the fifth section, the simulation results with synthetic data are presented. Finally, the discussion, conclusion, and future suggestions sections summarize the findings and future development directions.

2. Literature review

The digitalization of healthcare has accelerated at an unprecedented pace in the last decade, bringing concepts such as personalized medicine, targeted therapy, and clinical simulation to the forefront of researchers and technology companies. One of the fundamental concepts that has emerged in this regard is digital twins. A digital twin is essentially a virtual model of a living organism or real biological system that simulates the current and future state of that system by receiving continuous and up-to-date data from various sources [6]. This concept was already well-known in engineering and industry; however, in recent years, its introduction into the healthcare space has led to the formation of a new approach to the design, evaluation, and optimization of treatment pathways [7].

Studies have shown that the use of digital twins can play a role in optimizing clinical care, monitoring chronic diseases, designing personalized interventions, and even accelerating drug development [8]. One of the most significant achievements of this technology is the creation of systems that can receive individual patient data in real time and produce an active digital version of their biological state; a version that has the ability to learn, predict and suggest treatment pathways [9]. This approach has had significant applications in fields such as cardiovascular, cancer, diabetes and neurological diseases [10].

Alongside these advances, another rapidly growing technology has the potential to enhance the computational and analytical capabilities of digital twins: neuromorphic computing. Unlike conventional AI systems that rely on serial processing units, neuromorphic architectures design hardware and algorithms to mimic the functioning of neurons and synapses in the human brain [11]. This technology enables real-time processing, adaptive learning, and multimodal data analysis with lower power consumption, making it a great choice for situations that require immediate and contextual responses [12].

In healthcare, neuromorphic architectures have been used in applications such as EEG signal analysis, early diagnosis of neurological diseases, brain-computer interfaces, and behavioral monitoring [13]. Combining this technology with digital twins could be a step further towards a more complete and in-depth simulation of an individual's biological and psychological state. Unlike many traditional AI models that rely on past data, neuromorphic systems can continuously learn from new data and maintain their adaptability [14].

However, most existing digital twins are still based on classical numerical or deep learning models that are static, non-interactive, and dependent on historical data [15]. In many cases, these models lack the ability to understand the momentary behavioral and neurological changes in patients. For example, in situations where a patient experiences mood swings, sudden anxiety, or an unexpected response to medication, a traditional digital twin may not be able to react in time or modify the treatment course [16].

Furthermore, a serious challenge in designing digital twin-based therapeutic systems is their ability to handle multimodal and unstructured data. Data such as sleep patterns, mood states, stress levels, or behavioral responses to

medication require algorithms that can analyze them dynamically and contextually. In such a context, neuromorphic computing is not only an advantage, but also a necessity [17].

Based on this context, the need for a new model that can take advantage of the integration of digital twins with neuro-inspired computing is strongly felt. A framework that is not only able to analyze physiological, genetic, and pharmacological data, but also can involve the cognitive, psychological, and behavioral states of the individual in predicting treatment. The present study is designed to respond to this need by introducing the conceptual model NeuroTwinceutics™; A model that uses three main components (NeuroCore, TwinEngine, and Pharmaco-Loop) to create a dynamic and personalized digital profile of the patient's condition [18].

In this model, NeuroCore, as a neuromorphic processing core, analyzes multi-source data in real time, while TwinEngine provides an accurate digital representation of the individual's biological system, and Pharmaco-Loop continuously monitors and regulates the interaction between the drug, the body, and the nervous system. Such a structure allows the model to not only passively monitor the patient's condition, but also actively and in a timely manner provide suggestions for changing the treatment path, drug dosage, or even the type of intervention.

Thus, NeuroTwinceutics can be considered the intersection of two major technological trends: human-centered digital twins and neuro-centered computing. In the remainder of this article, the conceptual dimensions, implementation architecture, initial simulation results, and future development paths of this framework will be examined.

3. NeuroTwinceutics Conceptual Framework

The concept of NeuroTwinceutics is born from the convergence of three leading fields: neuromorphic computing, digital twins, and personalized pharmacology. In this framework, the goal is to provide a novel answer to the perennial challenge of predicting drug responses at the individual level. Unlike conventional digital twins, which are often based on static models or traditional machine learning, NeuroTwinceutics seeks a living, adaptive, and neural-based representation of the human being; a model that not only records biological information, but also learns, analyzes, and reacts in a manner similar to the human brain.

At the heart of the framework is a unit called the NeuroCore. This processing core receives physiological, behavioral, and drug data from sensors or databases and continuously analyzes it. Unlike conventional processors, NeuroCore is based on a neuromorphic architecture, meaning it has a structure similar to the brain’s neural networks and can learn and analyze environmental changes, complex signals, and behavioral patterns in real time. This learning does not occur in batches or offline, but rather during continuous interaction with the user and in response to drug injections.

On the other hand, the central simulation engine, called TwinEngine, is responsible for accurately modeling the body’s state. Using information about the body’s structure, genetic characteristics, metabolic patterns, and the user’s mental state, this engine creates a unique digital image of the individual’s health. This digital image is in constant communication with NeuroCore and can respond quickly to changes; for example, if side effects occur or mood changes after taking a drug, the model is automatically updated.

The connection between the digital brain and the biological twin is established through a loop called the Pharmaco-Loop. This loop continuously monitors the drug flow simulator in the body, the absorption rate, the effectiveness, and the bio- and psycho-feedback. In this process, the model not only analyzes the drug effect, but also makes suggestions for dose modification, timing, or drug replacement if necessary. In this way, NeuroTwinceutics goes beyond a mere simulation model and becomes an active tool in therapeutic decision-making.

Overall, the NeuroTwinceutics conceptual framework shows how the intelligent integration of neuromorphic and digital twin technologies can create a model that goes beyond health monitoring; one that is capable of understanding, predicting, and actually interacting with the individual body’s state. This framework not only paves the way for a revolution in drug design and evaluation, but could also open new horizons in personalized medicine, mental health, and mobile technologies. To better understand the proposed conceptual structure, Figure 1 schematically depicts the three-layer architecture of NeuroTwinceutics.

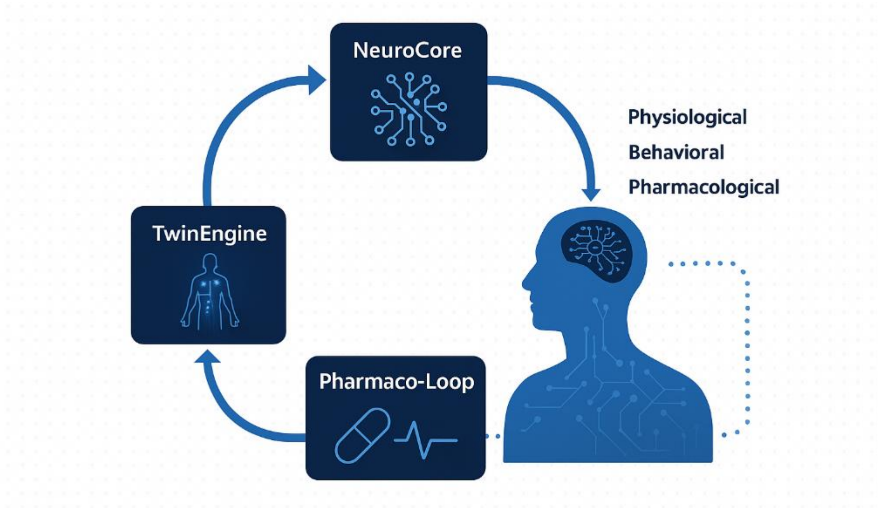

Figure 1. NeuroTwinceutics conceptual framework

As can be seen in the figure, the interaction between components is designed as a feedback loop that allows for adaptive learning and real-time response to biological changes.

4. Methodology and system architecture

The NeuroTwinceutics™ model is designed based on a three-layer architecture that synergistically communicates between the main components, namely NeuroCore, TwinEngine and Pharmaco-Loop. This architecture is designed to achieve an adaptive, real-time and personalized model in predicting drug response and uses neuromorphic technologies and continuous learning algorithms.

In the first layer, NeuroCore acts as the computational core. This core is designed based on neuromorphic architecture and uses brain-inspired structures (such as virtual synaptic networks and digital neural units) to process data. Input data includes physiological signals (such as heart rate, oxygen level, body temperature changes), behavioral information (such as sleep, physical activity, stress) and pharmacological data (dose, type of drug, time of administration). This data can be fed live from wearable devices or medical databases. NeuroCore analyzes this data using adaptive learning algorithms (such as STDP or Hebbian learning in a neuromorphic framework) and continuously updates the model.

In the second layer, TwinEngine acts as a digital simulator of the human body. It uses structural data, medical history, genetic patterns, and metabolic characteristics of the individual to generate a unique digital twin. The main difference between this engine and traditional digital twins is that its behavior is directly influenced by the NeuroCore and can dynamically respond to new conditions. Also, if historical data on drug use is available, TwinEngine can provide more accurate predictive models.

In the third layer, Pharmaco-Loop simulates an intelligent feedback loop between the drug and the body. This loop tracks the effects of the drug over time and, by monitoring biological and neurological responses, provides the ability to detect deviations from the optimal state. If the model detects unwanted effects or drug inefficiency, it can make suggestions for adjusting the dose, changing the drug, or modifying the schedule.

For the initial implementation of this framework, environments such as Nengo or Brian2 can be used for neuromorphic simulation, and Python with PyTorch for data management, network structure, and TwinEngine development. In the experimental step, synthetic data generated based on common clinical patterns were used to test the model performance and different drug usage scenarios (e.g., antidepressants or antiepileptics) were investigated in hypothetical patients.

The architecture is designed to be able to be linked to real healthcare systems (such as telecare systems or clinical systems). It is also modular and can be extended to other healthcare applications, including chronic diseases, combination therapy, and environmental impact analysis.

5. Simulation results with synthetic data (case study)

To operationally evaluate the proposed NeuroTwinceutics™ framework, a simulated study was designed and implemented using synthetic data. In this scenario, the model was fed data from a hypothetical patient receiving an SSRI antidepressant over a 10-day treatment period. The input data included three key parameters: stress level (on a scale of 1–10), nightly sleep duration (in hours), and mood score (on a scale of 1–10). The data were entered into the system with a sampling period of every 6 hours, corresponding to 40 time intervals.

The data were generated using realistic statistical models and previous clinical reports and were designed to reflect the natural behavioral and physiological fluctuations of the patient during treatment. A summary of the input values is provided in Table 1.

Table 1. Synthetic data generated for a hypothetical patient over a 10-day treatment period

Time	Stress Level (1-10)	Sleep Duration (hrs)	Mood Score (1-10)
Day 1, 0h	6.383214	7.635504	4.948109152
Day 1, 6h	8.485732	7.534536	4.797958343
Day 1, 12h	7.300616	6.815783	4.852917519
Day 1, 18h	5.236169	6.925254	4.925334673
Day 2, 0h	6.679836	4.487774	5.152803059
Day 2, 6h	6.601456	7.218505	5.032203282
Day 2, 12h	4.630551	7.189571	4.997232042
Day 2, 18h	6.720424	6.626249	5.202021494
Day 3, 0h	6.396266	5.562589	5.259761568
Day 3, 6h	7.40039	6.074705	5.418286278

After processing this data by the NeuroCore and creating a digital twin of the patient by the TwinEngine, the Pharmaco-Loop feedback loop took on the task of dynamically analyzing the drug response and predicting the patient’s psychological state. At this stage, the model generates an internal index called the “Stability Score,” which reflects the level of compliance of the individual with drug treatment. This numerical index is defined in the range [0, 1], and the closer its value is to 1, the more stable the individual’s neurobehavioral state is.

In cases where this score decreases or fluctuates significantly, the model automatically registers a suggestion for drug intervention (e.g., adjusting the dose, changing the schedule of administration, or considering a drug replacement). Figure 2 shows the trend of this stability score over time, with red dots indicating the moments when the model considered intervention necessary.

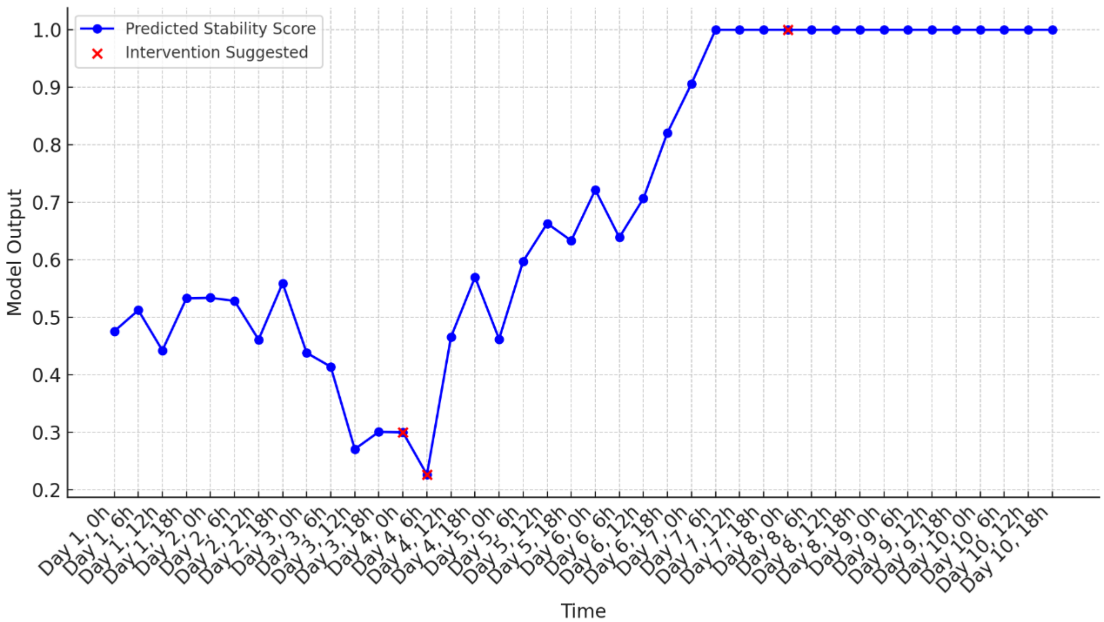

Figure 2. Output of the NeuroTwinceutics model including predicted persistence score and suggested drug intervention times over a hypothetical 10-day treatment period

As can be seen in Figure 2, fluctuations in predicted stability were recorded in the early days of treatment and the system suggested interventions at several time intervals. As the patient’s behavioral status improved, the stability trend increased and from the middle of the treatment period (after the seventh day), no interventions were suggested by the model. This indicates the model’s ability to adapt to the individual situation, analyze multidimensional data in real time, and make intelligent decisions based on neuromorphic architecture.

6. Discussion

Initial simulation results of the NeuroTwinceutics™ model demonstrate that this conceptual framework has the potential to analyze physiological, behavioral, and pharmacological data in real-time using a neural-centric approach. The use of neuromorphic architecture in the processing core (NeuroCore) has enabled the model to process information in a manner similar to that of the human brain, which allows the model to learn adaptively and respond in real-time to biological changes.

Unlike traditional digital twins, which are largely based on mathematical modeling or machine learning algorithms, NeuroTwinceutics is designed to be able to create drug feedback loops, continuously monitor the patient's condition, and predict the need for early intervention. This capability plays a critical role, especially in situations where the patient's psychological state or biological response is undergoing complex and subtle changes.

Another important advantage of this framework lies in its scalability. Although the main focus of this research is on the individual and clinical level, its modular and flexible structure also paves the way for development on an industrial scale. In this regard, the Australian-based company BIO10, which is currently investing in the design and development of advanced bioreactors, is exploiting frameworks such as NeuroTwinceutics to simulate biological reactions, optimize drug production processes, and intelligently control bioprocess systems. This convergence between neuromorphic digital twins and biomanufacturing infrastructure opens up new horizons in the evolution of industrial pharmaceutics and personalized medicine.

Despite these promising results, some limitations should be noted. The data used in this study are synthetic in nature, and the final evaluation of the model performance requires the use of real and diverse clinical data. Also, the practical implementation of this framework in medical or industrial environments requires the development of hardware platforms

compatible with neuromorphic processing and real-time communication infrastructures. However, the results of this study indicate that the combination of neuromorphic computing and digital twins can create a new path in the design of intelligent and adaptive medical systems.

7. Conclusion

In this study, an innovative framework called NeuroTwinceutics™ was introduced and analyzed; a framework that combines neuromorphic computing, digital twins, and drug response simulation, and is designed to improve accuracy and adaptability in personalized medicine. Unlike traditional methods, this model, using a neural-based architecture, is able to process patients' biological and behavioral data continuously and in real time and, if necessary, provide suggestions for optimizing the treatment path.

The results obtained from the simulation with synthetic data showed that NeuroTwinceutics has the ability to analyze dynamic changes in the patient's psychophysiological state and can predict and suggest therapeutic interventions in the face of critical fluctuations. Another important feature of this framework is its scalability from the individual level to industrial applications, so that it can be used in the future in biomanufacturing processes and complex simulation of pharmaceutical bioreactors.

Despite these achievements, the practical use of the model in clinical and industrial settings requires several complementary steps. First, testing the model with real patient data and measuring its accuracy in field conditions; second, developing hardware infrastructures to implement neuromorphic computing in clinical settings; and third, designing safe, transparent, and understandable user interfaces for healthcare professionals or pharmaceutical industry professionals.

In the future, the development of this framework can be pursued in three parallel directions:

1. Enhancing the model using multi-modal data, including genomic, psychological, and environmental information;
2. Linking with telecare infrastructures and mobile diagnosis systems;
3. And creating optimized versions for specific applications such as the treatment of resistant depression, chronic diseases, or customized drug production.

Ultimately, NeuroTwinceutics can be considered an initial and fundamental step towards creating a new generation of adaptive therapeutic systems that seek to bring neural intelligence to the heart of the medical decision-making process.

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